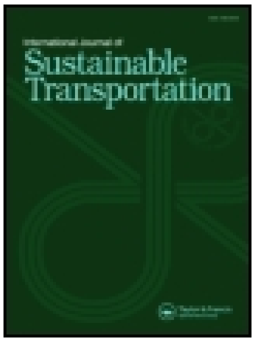

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New mobility service users' perceptions on electric vehicle adoption

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ABSTRACT
The recent growth of new mobility services such as car-sharing (ZipCar, Car2Go) and ride-hailing (Uber, Lyft) has interesting implications for new vehicle technologies. We explore the users of the services and their relation to electric vehicles preferences by analyzing two large-scale mobility service surveys. A number of categories (car-share usage, ride-hail usage, commute mode, demographics, current vehicle attributes, environmental attitudes, technology attitudes, and life-stage information) are examined in order to determine the likelihood a respondent considers purchasing an electric vehicle in the future. Survey respondents explicitly expressed that exposure to ride-hailing did not increase their propensity for wanting to purchase an electric vehicle in the future. However, we run a full suite of cross-validation models and find that in addition to the typical factors used in modeling preferences, the use of new mobility services statistically increases the predictive power of our model to identify preferences for electric vehicles.

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Car-sharing; electric vehicles; new mobility; ride-hailing; ride-sharing

1. Introduction

Electric vehicles (EVs) have been rapidly growing throughout the world. From essentially no commercial electric vehicles on the road a decade ago, EVs have well over a million vehicles worldwide today. This work is primarily focused on EV adoption in the United States due to the nature of the surveys and data used, but the results may have qualitative implications on the international scene as well. In the United States, the advent of commercial EV technology began in December of 2010 with the introduction of the Chevrolet Volt, a plug-in hybrid electric vehicle (PHEV), and the Nissan Leaf, a purely battery electric vehicle (BEV). While growth of the technology has been steady with over 30 models available in the United States at the beginning of 2016, market acceptance of EVs has been relatively low. In California, the highest proportion of EVs, the market share has not exceeded 3%; the adoption rate in most other states is significantly lower (ZEV Sales Dashboard, from https://autoalliance.org/energy-environment/zev-sales-dashboard/). Our work seeks to understand the perceptions and preferences of both EV owners and non-owners, particularly how they may be influenced by use and exposure to car-sharing and ride-hailing services such as Zipcar and Uber/Lyft respectively. Specifically, we hypothesize a positive correlation between these new mobility services and electric vehicle adoption. It may be that users who are willing to use car-sharing and ride-hailing services are more open to adopting new technologies such as electric vehicles. Our study attempts to integrate the usage of these services along with traditional methods of understanding EV purchase preferences as seen in the modern literature. We are able to determine whether or not specific services can help better map preferences for EVs and if users of the services are more or less likely to adopt the new technologies.

2. Literature review

Since car-sharing and particularly ride-hailing services are relatively new, the available literature is in short supply. Even the term "ride-share" can encompass many different types of services as pointed out by Furuhata, Maged, Fernando, Marc-Etienne, Xiaoqing, and Sven (2013) who classifies a number of ride-sharing agencies on the basis of the target market, service type, search criterion, matching activity, pricing, and payment method. Furuhata ultimately categorize the sharing as dynamic real-time ridesharing, carpooling, long distance ride matching, one shot ride matching, bulletin board, and flexible carpooling. One of the largest focuses in the literature on ride-hailing is their potential impact on the environment through its disruptive change on travel demand, though the direction of demand is still uncertain (Santi et al., 2014, Fagnant and Kockelman 2014, Jung, Jayakrishnan and Choi 2015, Rodier, Alemi and Smith 2015, Kim, Joonho and Yujin 2015, Kuemmerling, Christian and Gerrit 2013; Teubner and Christoph 2015). Other works include case studies examining the relational effects on taxi services in San Francisco (Rayle, Danielle, Nelson, Robert, & Susan, 2016) and in Chicago and New

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York City (Wallsten, 2015). In addition to these groups of works, there are a few notable individual pieces. One study examines how the intersection of policy and new mobility services will likely become an important issue in order to achieve a mutual goal of sustainable transportation (Cohen and Kietzmann 2014). Another study looks at the overall potential for ride-sharing services by identifying the opportunities for shared rides (Bicocchi and Mamei 2014). Lastly, and most relevant to our work, Kim et al. (2015) examined the role of exposure to electric vehicle sharing programs (EVSP) on preferences towards the technology in Korea. The authors use a survey on a population of EVSP users and develop models to measure their attitudes toward willingness to dispose of a car, willingness to purchase an EV, and willingness to continue participating in the EVSP. They find that social and economic factors are the most important factors for determining attitudes over EVSP preferences.

Our work also contributes to the body of literature on electric vehicle preferences. We first point to a recent relatively comprehensive review of these studies conducted by Rezvani, Johan, and Jan (2015), particularly focused on barriers to adoption of the technology. Different studies point to different sets of attributes as the most important when it comes to EV preferences. On the vehicle side: price and range (Krupa, et al., 2014, Franke and Krems 2013, Axsen and Kurani 2013, Degirmenci and Breitner 2017, Cheron and Michel 1997, Sierzchula, Sjoerd and Bert van 2014), environmental benefits and charging Heyvaert, Coosemans, Van Mierlo, & Macharis, 2015, and other vehicle attributes (Hackbarth and Madlener 2016, Hafner, Walker and Verplanken 2017, Shin, Chandra, Daehyun, Venu, & Ram, 2015, White and Sintov 2017). On the consumer side: income, being environmentally sensitive, education, and previous owners of hybrids (Carley, Rachel M., Bradley W., & John D., 2013, Axsen, Bailey and Castro 2015, Axsen, Orlebar and Skippon 2013, Noppers, Keizer and Bolderdijk, et al. 2014, Noppers, Keizer and Bockarjova et al. 2015, Hahnel, Golz and Spada 2014, Plotz, Uta, & Elisabeth, 2014, Cirillo, Liu and Maness 2017, Hardman, Eric and Robert 2016; Jakobsson et al. 2016). Similar to the aforementioned studies, our work primarily focuses on the consumer side attributes such as basic demographics (income, education, age, gender) as well as environmental attitudes. The novelty of our study is that it also takes into consideration factors that may be affected by new mobility services usage and familiarity.

3. Data: Survey overview

Two surveys were designed by a collaborative team that included researchers from Stanford, UC Davis, and Toyota Research Institute of North America (TRINA). Both surveys were administered via the online platform "Survey Analytics" and the samples of respondents were purchased through "qSample." The two surveys were designed and administered in the United States for the purposes of generally understanding car-sharing and ride-hailing services. In both surveys, a number of questions were asked about electric vehicle adoption and usage, which provided the primary data for this analysis. In the following sections, we quickly outline the two surveys used for this study followed by brief descriptions of data from the surveys that are necessary to conduct this study. Clewlow and Mishra (2017) also examined the same survey but with a focus on the impacts of new mobility services and their disruption on traditional transportation services.

3.1 *Survey A: Car-sharing survey*

The first survey was primarily aimed at collecting data on people with either familiarity or had adopted traditional car-sharing services. A pilot was deployed from September 2014 through October 2014 with the finalized survey being conducted from November 2014 through March 2015. The survey was conducted in urban ZIP codes of Boston, Chicago, Seattle, Washington D.C., and New York City with oversampling on car-sharing members by selecting ZIP codes with a significant number of Zipcar locations and a requirement to the sampling firm to include car-sharing members.

3.2 *Survey B: Life-stage and ride-hailing survey*

The second survey was a follow-on study that was more focused on on-demand services (such as Uber and Lyft) and additionally included a more extensive section on life-stage events. The survey was conducted from August 2015 through December 2015. The survey included both urban and suburban ZIP codes in Boston, Chicago, Washington, DC, New York City, San Francisco, and Los Angeles.

3.3 *Survey details*

3.3.1 *Preference for electric vehicles*

Respondents were surveyed on their consideration for purchasing an electric vehicle or hybrid vehicle for their next car. The distribution of respondents in both surveys can be seen in Figure 1. In survey A, the mode for all three technologies (HEV/PHEV/BEV) is the middle of the Likert scale "might or might not consider." For PHEVs and BEVs, the distribution is relatively symmetric around the mode, whereas there is a clear preference for considering HEVs in the future. In survey B, again the mode for all three technologies is also in the category of "might or might not consider." Although the cities surveyed in survey A and survey B are not the same, the difference in distributions was still observed even when we broke down the distributions by city to account for the three cities that did not overlap between surveys.

3.3.2 *New mobility usage*

The primary focus of our analysis is the influence of new mobility services on preferences for electric vehicles. We primarily focus on usage of the mobility services and whether different usage frequencies influence a respondent's intent to purchase an electric vehicle in the future. In the two surveys, respondents were asked about their frequency of use for car-sharing (survey A) and ride-sharing (survey B) in the last three months from when they took the survey.

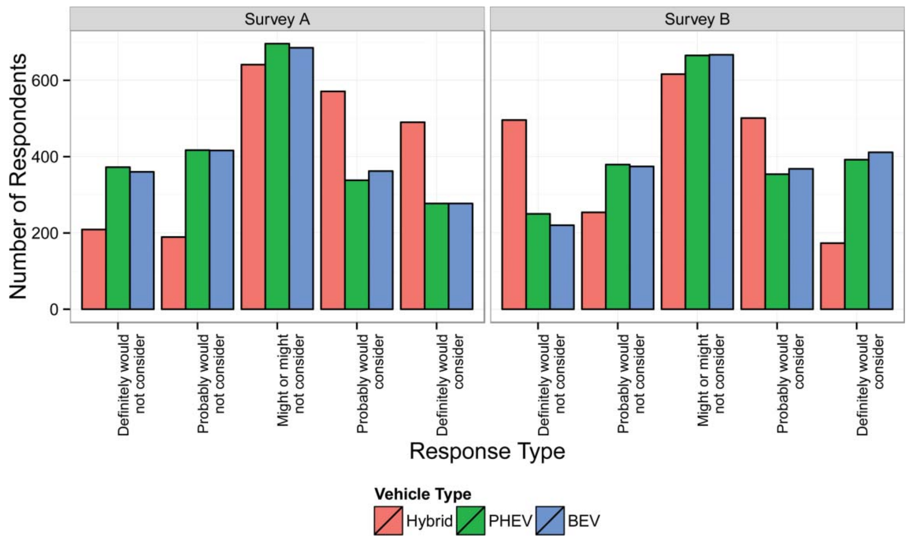

Figure 1. Stated preference for future purchase of a HEV/PHEV/BEV following the question: "For your next vehicle purchase would you consider any of the following types of vehicles?".

These frequencies are displayed in Figure 2. In both car-sharing and ride-sharing frequencies, the distribution of usage is skewed towards lower usage. We found in survey A, despite targeting users of car-sharing services, the majority of users do not use car-sharing. Similarly, for ride-sharing services the majority of the respondents use the services infrequently, though respondents tend to use Uber more frequently than Lyft.

Table 1. Demographic summary statistics for survey A.

Cities		Boston	Chicago	NY	Seattle	DC
Age	Mean	44.3	46.2	47.8	47.9	47.4
	Min	18	19	18	18	18
	Max	83	87	88	92	98
	SD	16.4	15.6	15.9	15.6	16.6
Gender	Male	43%	43%	47%	40%	45%
	Female	57%	57%	53%	60%	55%
Education	No college degree	8.3%	4.8%	6.1%	5.1%	5.4%
	Bachelor's degree	51.3%	60.0%	54%	60.7%	49.7%
	Graduate degree	40.4%	35.2%	39.9%	34.2%	44.9%
Employment	Full-time	55.1%	61.6%	54%	53.3%	58.4%
	Retired	12.7%	14.5%	15.3%	17.1%	17.7%
	Other	32.2%	23.9%	30.7%	29.6%	23.9%
Income	Under \$50 k	25.5%	21.4%	18.8%	23.2%	19.9%
	\$50 k-\$100 k	31.6%	35.4%	27.2%	35.5%	27.4%
	Over \$100 k	42.9%	43.2%	54.0%	41.3%	52.7%
Count		408	435	426	409	423

3.3.3 *Demographics*

A basic summary of demographic information is provided in Tables 1 and 2. In reference to the true population, we observe several demographic distinctions:

- Older population sampled
- Biased towards females
- More educated than average
- Higher income than average

A Kolmogorov–Smirnoff test of age, gender, education, and income all demonstrate that the distributions are statistically different (all with p-values above 0.1). In terms of comparison between the respondents in survey A and survey B, we find that ages are similarly distributed. The mean age ranges from the mid to late forties in all cities, the distribution of respondents

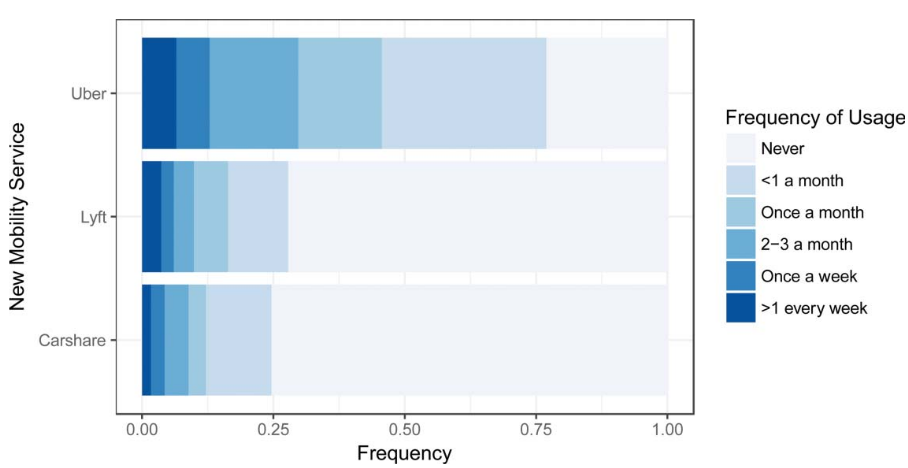

Figure 2. Histogram of new mobility usage frequencies from surveys A (car-share, $n = 2100$) & B (ride-share, $n = 629$). Responses are based on the past 3 months at the time the survey was administered.

Table 2. Demographic summary statistics for survey B.

Cities		Boston	Chicago	L.A.	NY	SF	DC
Age	Mean	46.7	47.6	46.7	48.0	49.8	49.2
	Min	18	18	18	18	18	18
	Max	90	83	91	87	92	88
	SD	17.2	16.4	16.4	17.2	16.9	16.3
Gender	Male	39%	39%	36%	39%	42%	41%
	Female	61%	61%	64%	61%	58%	59%
Education	No college degree	8.3%	8.2%	5.4%	8.9%	3.7%	4.9%
	Bachelor's degree	67.2%	70.6%	78.3%	74.8%	70.8%	64.6%
	Graduate degree	24.5%	21.2%	16.3%	16.3%	25.5%	30.5%
Employment	Full-time	32.2%	34.7%	37.1%	37.6%	36.3%	37.3%
	Retired	11.7%	13.6%	16.0%	11.4%	18.5%	13.0%
	Other	56.1%	51.7%	49.9%	51.0%	45.2%	49.7%
Income	Under \$50 k	17.1%	20.1%	20.5%	16.3%	15.3%	14.3%
	\$50 k-\$100 k	54.1%	56.2%	45.5%	52.4%	42.7%	49.5%
	Over \$100 k	28.8%	23.7%	34.0%	31.3%	42.0%	36.2%
Count		351	354	606	361	615	370

are slightly older than the true age of the population. The gender discrepancy towards females is slightly larger in survey B with survey A hovering in the mid-50th percentile while survey B is in the low 60th percentile. In terms of education, those without a college degree are relatively similar between both surveys but there are a higher proportion of respondents with graduate degrees in the first survey compared to the second. On the basis of employment, there are fewer full-time employees in survey B compared to survey A, though the retirement figures are relatively close. Lastly, in the category of income, survey A is biased toward higher income whereas survey B has a large clustering in the mid-range between $50,000 and $100,000. It should be noted that the results are biased towards the sampled population rather than the actual population seen in each of the respective cities. We do not expect our results be broadly applied to the population of the cities contained in the surveys but rather whether prediction of EV preferences can be made based on similar surveys.

3.3.4 *Vehicle matching*

Both surveys asked for information about respondents' current vehicle. Using this information, we are also able to investigate whether the current or previous vehicles can be used to help determine preference for the future choice of an electric vehicle. The respondents' household vehicle entries of make, model, and year were matched to a VIN database containing vehicle characteristics. The matching was conducted with a fuzzy matching algorithm minimizing Levenshtein's distance (Levenshtein, 1966) in order to combine the survey data with vehicle attribute information such as fuel economy, manufacturer's suggested retail price (MSRP), and vehicle class. These attributes are then used as one of categories of investigation in modeling electric vehicle purchase preferences.

4. Method

Our study attempts to understand some of the determinants behind respondents' stated preference for their future preference of purchasing an electric vehicle. We approach this in three ways: (1) analyzing a stated response for factors influencing a purchase, (2) a set of multinomial logistic models across a variety of categories, and (3) running a suite of models through a cross-validation algorithm. The first approach simply assesses a direct response in the survey. The latter two approaches are described in the following sections 0 and 0, respectively. We apply three approaches in order to investigate whether different methods reveal robust results. In the first approach, new mobility can be determined to be a causal factor in the preference for electric vehicle purchases because the respondents are elicited directly in a stated-preference form. In the latter two approaches, the revealed-preferences are leveraged in our analysis to see whether the results are consistent.

4.1 *Multinomial logistic regression models on sets of categories*

We employ a standard multinomial logistic regression model to calculate the probability that a respondent will choose each category in the Likert scale of responses seen in Figure 1. The probability π varies across each of the Likert choices j and across each the values i of each variable x in the function shown in equation (1).

$$\pi_{ij} = \frac{\exp(\beta_j x_i)}{\sum_k \exp(\beta_k x_i)} \qquad (0)$$

We run the model in equation (0) over several categories, each representing a separate set i:

- Car-share usage (survey A)
- Ride-hail usage (survey B)
- Commute type (both surveys separately)
- Demographic set: age, income, education, and city (both surveys together)
- Previous vehicle attributes: MSRP, vehicle class, and fuel efficiency (both surveys together)
- Life-stage clusters: age, employment, and children (survey B)
- Attitudes about environment and technology (both surveys together)

Asides from the car-share and ride-hail usage (meant to test our primary hypothesis), our choice of variables to investigate are based on common variables for EV adoption preferences in the literature. As seen in the literature review in Section 0, we include demographic variables and attitudes about environment and technology for consumer centric preferences while we include vehicle attributes for vehicle centric preferences. It is important to include these variables because they have been previously established to influence EV preferences. All variables are introduced as dummy variables with the exception of numerical variables of age, MSRP, fuel efficiency, and attitudes about environment and technology. For each category, we run all the variables listed, but our final results omit variables where no variance in preference is seen over the range of the variable. Furthermore, our analysis runs the model to obtain a separate set of probabilities, π_{ij}, for BEV preferences and for PHEV preferences.

The life-stage clusters are obtained using a k-means clustering algorithm to group the data into clusters. We chose the variables of age, employment, and whether or not the respondent has children to represent the life-stage of the respondent. The clusters allow us to observe nonlinear trends that is focused on the grouping of several variables that help to define the stage of life a respondent is currently in.

The environment and technology attitudes are based on ordinal scales (ranging on a five-point scale from strongly disagree to strongly agree). The environmental attitudinal questions are comprised of six equally weighted responses to the following statements:

- "I believe my actions can make a difference for the environment."
- "I would switch to a different form of transportation if it would help the environment."
- "It takes too much time and effort to do things that are environmentally friendly."
- "It is pointless for me to try too hard to be more "green", because I am just one person."
- "I believe in doing more than my share to reduce our impact on the environment."
- "I am reluctant to sacrifice to help the environment, if other people aren't doing it too."

The reliability of the scale (Cronbach $\alpha = 0.78$) allows us to construct a scoring mechanism based on the sum of the respective attitudinal scores (translating the ordinal scale to a 1–5 scale). Likewise a score is constructed from technological attitudinal scale (Cronbach $\alpha = 0.59$) based on four attitudinal statements:

- "Purchasing the latest and greatest tech gadget is a waste of money."
- "I would be nervous about purchasing an electric vehicle."
- "I like to track the development of new technology."
- "I would consider myself to be tech savvy."

4.2 *Determining variable importance through cross-validation*

In addition to running the model across the different categories, we also attempt to identify the most important variables for the purposes of prediction. To do this, we conducted a 5-fold cross-validation of the model described in equation (0), across all possible combinations of variables against both BEV preferences and PHEV preferences, as well as for survey A and B separately. This k-fold cross-validation model is a common technique in calibrating machine learning model algorithms but can be applied in this case to establish the best predictive model (Bengio and Grandvalet 2004, Kohavi, 1995, Rodriguez, Perez and Lozano 2010). Each specification randomly divides the data into five separate slices (for example, "a, b, c, d, e"), the model is then calibrated using four of the slices (i.e., a, b, c, d) and then predicts the probabilities associated with each preference using the final slice (e). We then assign a score based on a constructed scoring system:

$$\mathrm{score}_j = 5 - |y_j - {}^{y}{}_j|\pi_{ij} \qquad (0)$$

The score measures the nominal distance between a predicted outcome (^{y}) and the actual outcome (y), weighted by the probability (π) associated with each predicted outcome. This quantity is reversed by subtracting away from 5 (the maximum distance) so that a higher score represents a more accurate model. The validation model is run five times for each specification set (so a score is obtained for each a, b, c, d, e) and the average of the five scores is the final score for the particular specification. The maximum score that can be achieved is 5 if any particular model exactly predicts the respondents' future purchasing preference for EVs. As one model's prediction becomes less accurate, it will receive a progressively lower score. In this manner, we are able to construct a full set of models using combinations of all variables to determine which models perform the best in terms of out-of-sample prediction.

The scoring procedure is run across 2,040 combination of variables to obtain a set of scoring clusters for all possible models. The purpose of obtaining a complete set of scores is to identify (1) the best out-of-sample predictive model and (2) the most important variable or set of variables to obtain accurate predictions. We note that our cross-validation model is not completely comprehensive; due to limitations in data from the survey we are unable to include certain variables such as those related to range preferences or charging availability of electric vehicles.

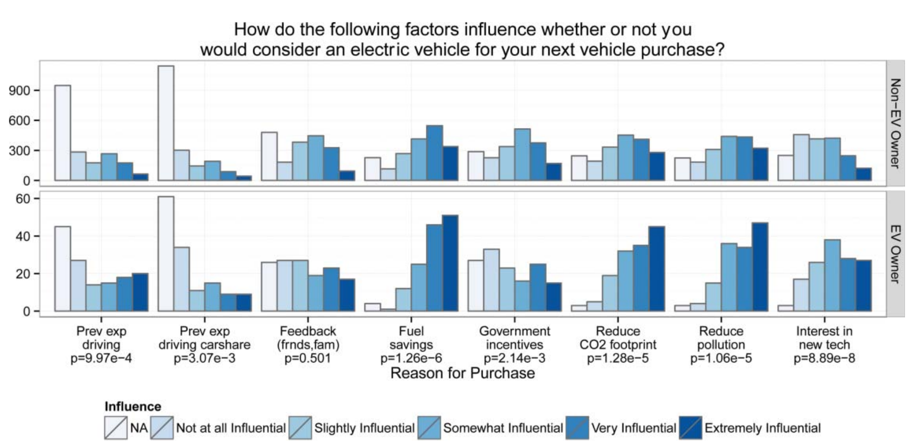

Figure 3. Survey A—respondents' reasons for considering an EV for purchase, split by first-time buyers (top, $n = 1913$) and current owners (bottom, $n = 139$). The p-values represent differences between distributions for EV owners and Non-EV owners as measured by Kolmogorov–Smirnoff tests (null hypothesis that the distributions are the same). Abbreviations: Prev = Previous, exp = experience, frnds = friends, fam = family, tech = technology.

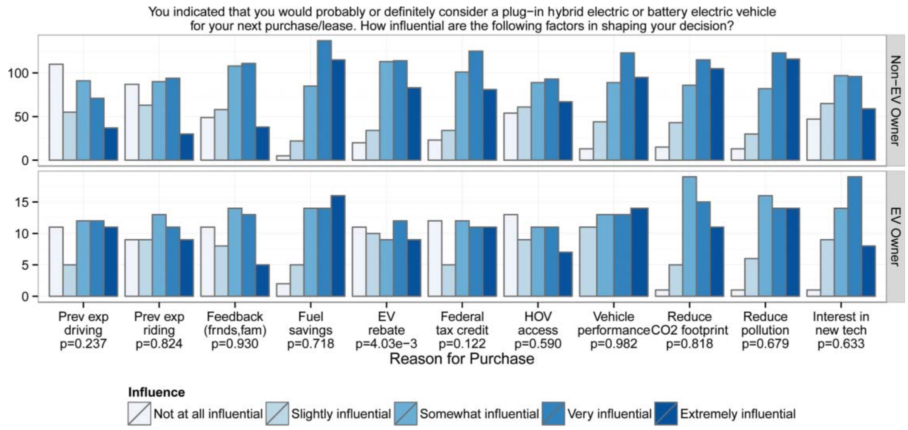

Figure 4. Survey B—respondents' reasons for considering an EV for purchase, split by first-time buyers (top, $n = 364$) and current owners (bottom, $n = 51$). The p-values represent differences between distributions for EV owners and Non-EV owners as measured by Kolmogorov-Smirnoff tests (null hypothesis that the distributions are the same). Abbreviations: Prev = Previous, exp = experience, frnds = friends, fam = family, HOV = high occupancy vehicle lane, tech = technology.

5. Results

5.1 *Stated factors affecting preferences*

In both surveys, respondents were asked to identify factors that influenced whether or not they would consider purchasing an electric vehicle for their next vehicle purchase. This particular section focuses on the causal relationship between exposure to new mobility services and ownership or potential ownership of electric vehicles. The frequencies of each response for the factors in the survey are shown in Figures 3 and 4. Besides the differences in the listed factors between survey A and B, the question in survey B was additionally asked only to respondents who stated that they would "definitely" or "probably" consider purchasing an electric vehicle in the future. Therefore, Figure 4 is biased toward respondents who are more likely to purchase an electric vehicle while Figure 3 applies to the entire respondent population of survey A.

Figure 3 is divided into two groups, the top set represents a larger set of respondents who have not owned an electric vehicle, whereas the bottom set represents a smaller set of respondents who currently own or have previously owned an electric vehicle. The response distribution is somewhat similar between the two groups with the exception that the current owners of electric vehicles place more importance on fuel savings, reducing CO2 footprint, and reducing pollution than those who do not currently own an electric vehicle. In Table 3, the reasons motivating the purchase of an electric vehicle are collapsed into a ranked list based on the response in the survey (highest score prescribed to "most influential" and lowest score prescribed to "least influential"). The table shows that fuel savings, reduction of CO_2, and reduction of pollution are the top reasons why an EV would be purchased while experience driving through car-share or general experience driving are the least important reasons.

Since the respondent set in Figure 4 consists of likely purchasers of electric vehicles, their attitudes toward the technology are likely more similar to those who have already purchased them. This effect is observed in the responses in survey B as the distributions for each factor are more similar between the two groups "may purchase" and "have purchased" than in survey A. We also examine the distributions by city in order to ensure that the difference in responses between survey A and survey B is not a result of the different cities that were surveyed. The non-overlapping cities do not account for the discrepancy between the surveys. Likewise to survey A we produce an ordered ranking of reasons in Table 4 with nearly identical results. The survey responses demonstrate that from a causal standpoint, issues of fuel savings and environmental reasons (reducing carbon footprint and pollution) are the primary motivators for purchasing an electric vehicle, not exposure to car sharing or ride hailing services.

Table 3. Ranked order of importance for reasons for purchasing an EV in the future, weighted according to response type, survey A.

Ranking	Category	Weighted Category Score
1	Fuel savings	6,318
2	Reduce pollution	5,980
3	Reduce CO_2 footprint	5,758
4	Government incentives	5,101
5	Interest in new technology	4,582
6	Feedback (friends, family)	4,385
7	Previous experience driving	2,729
8	Previous experience driving carshare	1,921

Mean of weighted category score: 4,596.75
SD of weighted category score: 1,566.25

Table 4. Ranked order of importance for reasons for purchasing an EV in the future, weighted according to response type, survey B.

Ranking	Category	Weighted Category Score
1	Fuel savings	1,617
2	Reduce pollution	1,578
3	Reduce CO_2 footprint	1,527
4	Vehicle performance	1,518
5	Federal tax credit	1,456
6	EV rebate	1,449
7	Interest in new technology	1,324
8	HOV access	1,293
9	Feedback (friends, family)	1,269
10	Previous experience riding	1,164
11	Previous experience driving	1,122

Mean of weighted category score: 1,392.46
SD of weighted category score: 167.66

5.2 Multinomial logistic regression models for preference probabilities

In the following subsections, we focus on identifying attributes of the respondents that correlate with respondents' preferences for purchasing an electric vehicle in the future. We note that these relationships are not causal (e.g., new mobility service usage directly causes higher desire to purchase EVs) but allow us to understand the most important factors influence EV preferences.

5.2.1 Car-share and ride-hail usage

We calculate the probability for each preference choice of purchasing a BEV or a PHEV based on respondents' usage of car-sharing or ride-hailing services. Each line in Figure 5 (with corresponding MNL results in Tables 5 and 6) represents the probability for a particular preference choice as the frequency of car-share usage changes. The graph also shows the 95% confidence interval associated with the probabilities as the shaded ribbon around the line. For both BEVs and PHEVs, we find that as frequency of car-share usage increases, there is a corresponding increase in the probability that the respondent has a higher preference both in the "definitely would consider" and "probably would consider" categories. Similarly, there is a decrease in the "definitely would not consider" and "probably would not consider" categories. Similarly, we calculate the

Table 5. Multinomial logistic regression results for car-sharing model on the adoption of BEVs and PHEVs.

		Probably would not consider	Might or might not consider	Probably would consider	Definitely would consider
BEV purchase intention	Car-share usage	−0.012	0.105*	0.316***	0.533***
		(0.072)	(0.061)	(0.061)	(0.060)
	Constant	0.161	0.492***	−0.503***	−1.269***
		(0.122)	(0.108)	(0.121)	(0.134)
	AIC	6393.272			
PHEV purchase intention	Car-share usage	−0.015	0.086	0.302***	0.516***
		(0.069)	(0.059)	(0.060)	(0.058)
	Constant	0.135	0.502***	−0.587***	−1.279***
		(0.120)	(0.106)	(0.121)	(0.133)
	AIC	6380.58			

probabilities of each preference choice but for ride-hailing instead of car-sharing frequency of use for the second survey. The results for both BEVs and PHEVs are similar with an increase in probability for the higher preference choices "probably would consider" and "definitely would consider" as the frequency of ride-share (combined Uber and Lyft) use increases. The effect is slightly more pronounced for "probably would consider," though the uncertainty of probability also increases with higher ride-share use. Both "might or might not consider" and "probably would not consider" preferences level off in probability and decrease slightly while "definitely would not

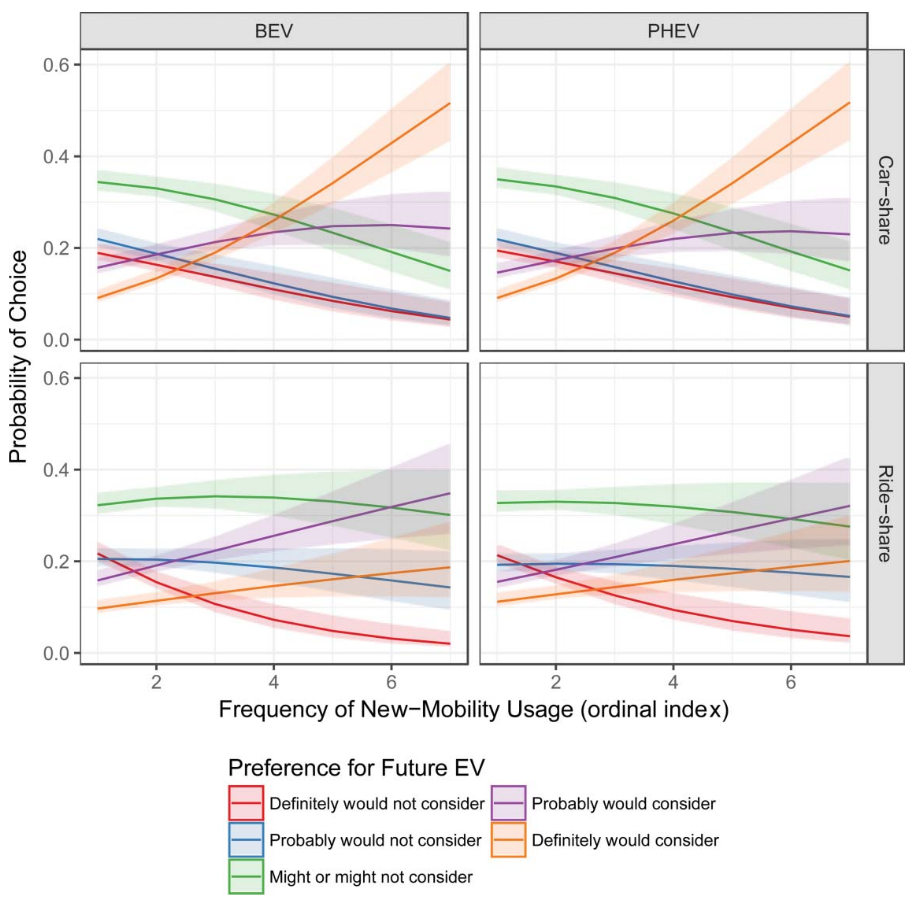

Figure 5. Car-sharing and ride-hailing vehicle electrification analysis, predicted probabilities for future BEV/PHEV purchase preferences based on car-share/ride-hail usage. Error bars on each line encompass a 95% confidence interval based on the standard errors from the model.

Table 6. Multinomial logistic regression results for ride-hailing model on the adoption of BEVs and PHEVs.

		Definitely would not consider	Probably would not consider	Might or might not consider	Probably would consider
BEV purchase intention	Uber/Lyft usage	−0.252***	−0.085***	−0.061**	0.011
		(0.042)	(0.032)	(0.029)	(0.030)
	Constant	0.809***	0.753***	1.205***	0.495***
		(0.098)	(0.098)	(0.091)	(0.101)
	AIC	6252.592			
PHEV purchase intention	Uber/Lyft usage	−0.195***	−0.061**	−0.063**	0.012
		(0.038)	(0.031)	(0.028)	(0.029)
	Constant	0.645***	0.542***	1.074***	0.327***
		(0.094)	(0.094)	(0.087)	(0.097)
	AIC	6304.613			

consider" rapidly decreases as frequency of Uber/Lyft usage increases. While the trend indicates that ride-share users have a higher preference for electric vehicles, it is not necessarily true that exposure causes higher acceptance for the technology. When directly asked to sort the importance of various reasons for their interest in purchasing a BEV or PHEV, respondents stated that exposure through car-sharing and ride-hailing programs played among the least influential role, as compared to other aspects such as fuel savings, impacts on the environment, and interest in new technology. The observed preference could be due to the fact that the types of people who use ride-hailing services happen to have higher acceptance for the new vehicle technologies. Regardless, the usage of the new mobility service provides another indicator for predicting EV preferences.

5.2.2 *Commute categories*

We measure changes in preference across different work commute types for BEVs and for PHEVs in Figure 6 (with corresponding MNL results in Tables 7 and 8). Each discrete commute choice has an associated probability for each preference level. We find only marginal differences in commute mode on the preferences between BEVs and PHEVs.

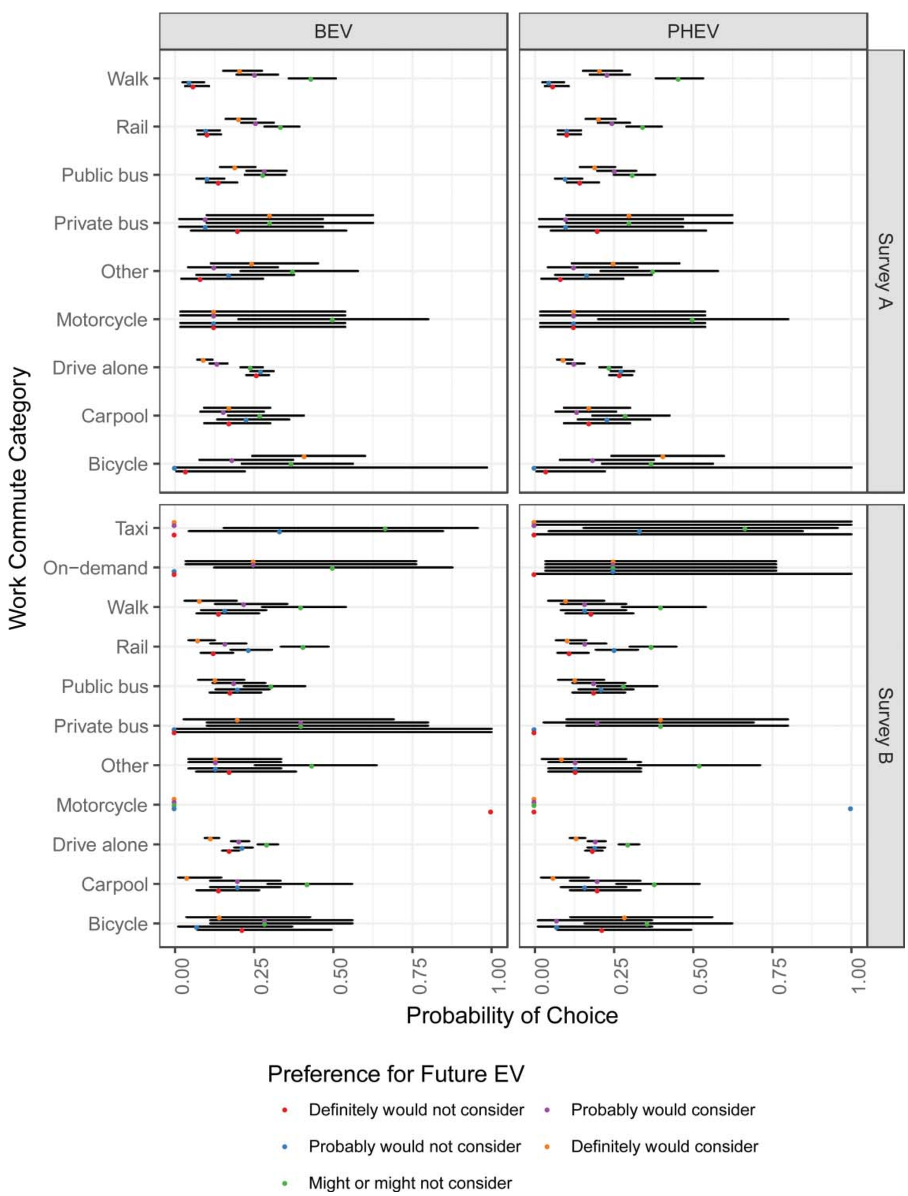

Figure 6. Commute type and vehicle electrification analysis, predicted probabilities for future BEV/PHEV purchase preferences based on commute type. Error bars on each line encompass a 95% confidence interval based on the standard errors from the model.

Table 7. Multinomial logistic regression results for commute categories model in survey A on adoption of BEVs and PHEVs.

	Commute Mode	Probably would not consider	Might or might not consider	Probably would consider	Definitely would consider
BEV purchase intention	Bicycle	−3.402	2.334**	1.629	2.440**
		(5.664)	(1.065)	(1.112)	(1.060)
	Carpool	0.274	0.448	−0.107	−0.001
		(0.442)	(0.427)	(0.485)	(0.471)
	Drive Alone	0.052	−0.077	−0.654***	−1.039***
		(0.114)	(0.118)	(0.140)	(0.160)
	Motorcycle	0.001	1.387	0.001	0.001
		(1.414)	(1.118)	(1.414)	(1.414)
	Other	0.741	1.514*	0.423	1.092
		(0.865)	(0.786)	(0.915)	(0.822)
	Private Bus	−0.708	0.409	−0.708	0.409
		(1.230)	(0.912)	(1.230)	(0.912)
	Public Bus	−0.299	0.693***	0.711***	0.315
		(0.295)	(0.236)	(0.235)	(0.253)
	Rail	−0.037	1.172***	0.906***	0.672***
		(0.265)	(0.212)	(0.220)	(0.228)
	Walk	−0.224	1.983***	1.453***	1.244***
		(0.473)	(0.336)	(0.350)	(0.358)
	AIC	4093.211			
PHEV purchase intention	Bicycle	−10.679	2.301**	1.608	2.397**
		(208.291)	(1.048)	(1.095)	(1.044)
	Carpool	0.288	0.511	−0.251	0.00004
		(0.441)	(0.422)	(0.504)	(0.471)
	Drive Alone	0.019	−0.130	−0.759***	−1.080***
		(0.113)	(0.117)	(0.142)	(0.159)
	Motorcycle	0.001	1.387	0.001	0.001
		(1.414)	(1.118)	(1.414)	(1.414)
	Other	0.694	1.505*	0.406	1.100
		(0.866)	(0.782)	(0.913)	(0.817)
	Private Bus	−0.693	0.406	−0.693	0.406
		(1.225)	(0.913)	(1.225)	(0.913)
	Public Bus	−0.388	0.762***	0.560**	0.279
		(0.297)	(0.229)	(0.237)	(0.250)
	Rail	0.00000	1.197***	0.867***	0.676***
		(0.263)	(0.212)	(0.221)	(0.228)
	Walk	−0.223	2.041***	1.361***	1.253***
		(0.474)	(0.336)	(0.354)	(0.359)
	AIC	4078.258			

For the commute categories of bicycles, motorcycles, public bus, and other: the standard errors of the predicted probabilities are too large to be able to distinguish any statistically significant differences in preference choices for the purchase of EVs. This is likely due to the fact that variance within a commute group is too high to predict purchase preferences (e.g., some who ride the bus would want an EV while other would not). A large majority of the respondents in survey A drive alone and the preference probabilities are significantly higher for not considering EVs in the future compared to considering EVs in the future. However, for the commute modes of public bus, rail, and walking we find that there is a statistically significant probability corresponding to higher preferences for purchasing an EV in the future. While the "might or might not consider" is the highest probability, both "probably would consider" and "definitely would consider" is higher than the probabilities for non-consideration.

In survey B, the preferences corresponding commute mode choice are much more varied than in survey A. In addition to the commute modes in survey A, the second survey also includes on-demand services and taxis as mode choices. The uncertainty ranges on biking, carpooling, on-demand services, taxi, and walking are too high to determine preferences for different choices. However, for the commute choices of driving alone, public bus, and rail the distribution of preferences is relatively even with similar probabilities for all the choices and slightly higher probability for the neutral "might or might not consider." In both surveys, it is difficult to predict future interest in purchasing a BEV or PHEV with commute choice as the sole predictive variable.

5.2.3 *Vehicle attributes*

In Figure 7, we explore whether attributes of respondents' current and previous vehicles provide any indication to the preference choice for BEVs and PHEVs (with corresponding MNL results in Table 9). While we tested for attributes including fuel efficiency, vehicle class, and MSRP, we found only variation occurred in the MSRP variable. The variation range was quite large, with the majority of vehicle MSRPs ranging from \$15,000 through \$80,000. We find that for BEVs the "might or might not consider" category increases as the MSRP of the current vehicle increases and the remainder of the categories uniformly decrease in probability. For PHEVs, all the preference levels remain relatively flat over different ranges of MSRPs but the "might or might not consider" preference level remains the highest probability choice. The predictive capability of the MSRP variable is relatively low, particularly for choices at either

Table 8. Multinomial logistic regression results for commute categories model in survey B on adoption of BEVs and PHEVs.

	Commute Mode	Definitely would not consider	Probably would not consider	Might or might not consider	Probably would consider
BEV purchase intention	Bicycle	0.405	−0.694	0.692	0.692
		(0.913)	(1.225)	(0.866)	(0.866)
	Carpool	1.253	1.609**	2.351***	1.609**
		(0.802)	(0.775)	(0.740)	(0.775)
	Drive Alone	0.417***	0.628***	0.937***	0.578***
		(0.138)	(0.133)	(0.126)	(0.134)
	Motorcycle	17.478	−3.753***	−3.753	−3.753***
		NaN	(0.000)	NaN	(0.000)
	On-demand	−13.013***	−13.013***	0.693	−0.001
		(0.00001)	(0.00001)	(1.225)	(1.414)
	Other	0.288	0.00001	1.204*	0.00001
		(0.764)	(0.816)	(0.658)	(0.816)
	Private Bus	−12.521	−12.521	0.693	0.693
		(523.655)	(523.655)	(1.225)	(1.225)
	Public Bus	0.310	0.435	0.860**	0.375
		(0.397)	(0.387)	(0.360)	(0.392)
	Rail	0.511	1.153***	1.705***	0.773**
		(0.365)	(0.331)	(0.314)	(0.349)
	Taxi	−5.716***	13.163***	13.856***	−5.716***
		(0.00000)	(0.612)	(0.612)	(0.000)
	Walk	0.560	0.693	1.609***	1.012*
		(0.627)	(0.612)	(0.548)	(0.584)
	AIC	3623.802			
PHEV purchase intention	Bicycle	−0.288	−1.387	0.223	−1.387
		(0.764)	(1.118)	(0.671)	(1.118)
	Carpool	1.204*	0.981	1.846***	1.204*
		(0.658)	(0.677)	(0.621)	(0.658)
	Drive Alone	0.327**	0.368***	0.801***	0.375***
		(0.131)	(0.129)	(0.120)	(0.129)
	Motorcycle	−3.211	14.844	−3.211***	−3.211
		NaN	NaN	(0.00000)	NaN
	On-demand	−11.508	−0.002	−0.002	−0.002
		(315.215)	(1.414)	(1.414)	(1.414)
	Other	0.407	0.407	1.793**	0.407
		(0.913)	(0.913)	(0.764)	(0.913)
	Private Bus	−14.003***	−14.003***	−0.00002	−0.693
		(0.00000)	(0.00000)	(1.000)	(1.225)
	Public Bus	0.375	0.493	0.780**	0.375
		(0.392)	(0.383)	(0.364)	(0.392)
	Rail	0.057	0.880***	1.261***	0.425
		(0.338)	(0.288)	(0.275)	(0.312)
	Taxi	−4.998	11.215	11.908	−4.998
		(3.655)	(270.637)	(270.637)	(3.655)
	Walk	0.588	0.470	1.386***	0.470
		(0.558)	(0.570)	(0.500)	(0.570)
	AIC	3655.171			

extreme (of wanting or not wanting to purchase an EV in the future).

5.2.4 *Life-stage clusters*

We use $k = 4$ in our k-means cluster analysis with a between sum of squares (BSS) to total sum of squares (TSS) ratio of 88.6%, indicating a good fit of clusters. The four groups consist of:

- Late 20's, employed, no children
- Mid 40's, employed, some children
- Late 50's, some employed, some children
- 70's, mostly retired, some children

Among the different life-stage clusters, there do not appear to be any particular clusters that tend to favor the adoption of either of the new technologies. In all clusters, the probability is highest for the neutral "might or might not consider" preference. For the middle clusters (ages 40's and 50's), the probability for both consideration and non-consideration are relatively even while the remaining clusters (ages 20's and 70's) tend to have higher probabilities for non-consideration (Figure 8 with corresponding MNL results in Table 10).

5.2.5 *Environment and technology attitudes*

The attitudinal scores in Figure 9 (with corresponding MNL results in Table 11) measure the environmental and technology attitudes of the survey respondents. The scores represent a quantitative index of a variety of survey questions on environmental concerns and aptitude of new technologies. Higher environmental attitudinal scores correspond to heightened environmental awareness and concern, while higher technology attitudinal scores correspond to familiarity and interest in new consumer technologies. For both BEVs and PHEVs, the preference category of "might or might not consider" has the highest probability of being chosen and increases as both environmental and technology scores increased. However, there is no substantial changes in the other preference categories, they decrease relatively uniformly as "might or might not consider" increases.

5.3 *Cross-validation and scoring of individual variables*

We were interested in understanding what the best possible model was for predictive purposes by combining the variables

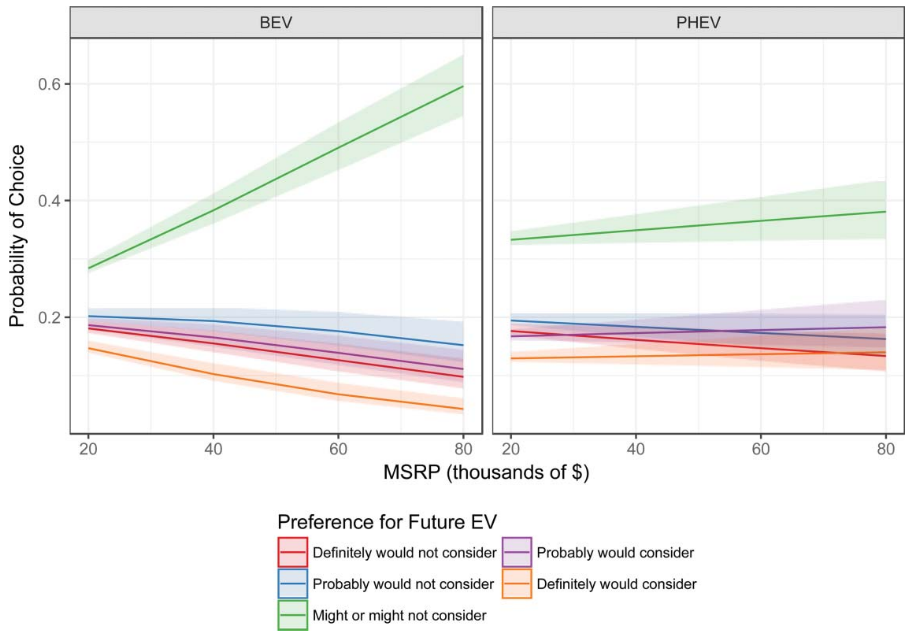

Figure 7. Previous vehicle manufacturer's suggested retail price (MSRP) and vehicle electrification analysis, predicted probabilities for future BEV/PHEV purchase preferences based on respondents' current vehicle MSRP. Error bars on each line encompass a 95% confidence interval based on the standard errors from the model.

Table 9. Multinomial logistic regression results for previous vehicle MSRP model on adoption of BEVs and PHEVs.

	Previous vehicle attributes	Probably would not consider	Might or might not consider	Probably would consider	Definitely would consider
BEV	MSRP ($1000 s)	0.00552**	0.0226***	0.00159	−0.0103***
		(0.00223)	(0.00199)	(0.00230)	(0.00256)
	AIC	9640.039			
PHEV	MSRP ($1000 s)	0.00167	0.00690***	0.00614***	0.00595**
		(0.00222)	(0.00197)	(0.00227)	(0.00242)
	AIC	6380.58			

in Section 0. An exhaustive set of 2022 models were run with different combinations of 10 selected variables in each survey A/survey B and BEV/PHEV preference breakdown. The scores of the cross-validated models are calculated as described in Section 0 and shown in Figure 10. In Survey A of Figure 10, there are three distinct clusters of scores. Our results indicate that for both BEV and PHEV preferences, the highest scoring cluster consistently contains several variables. Predictive power is typically highest when including the car-share use frequency, commute mode, and either/both city and education. In Figure 10 of survey B, the scores are grouped in a single distribution unlike the scores in survey A. However, we also find a similar requirement of variables that consistently are found in the highest set of scores. The most crucial variables include ride-hail use frequency, city, age, and either/both education and income. When we isolate the distribution of scores by variables in Figure 11, we find that asides from car-share usage and commute mode in Survey A, most of the variables are similarly grouped in their distributions of cross-validation scores.

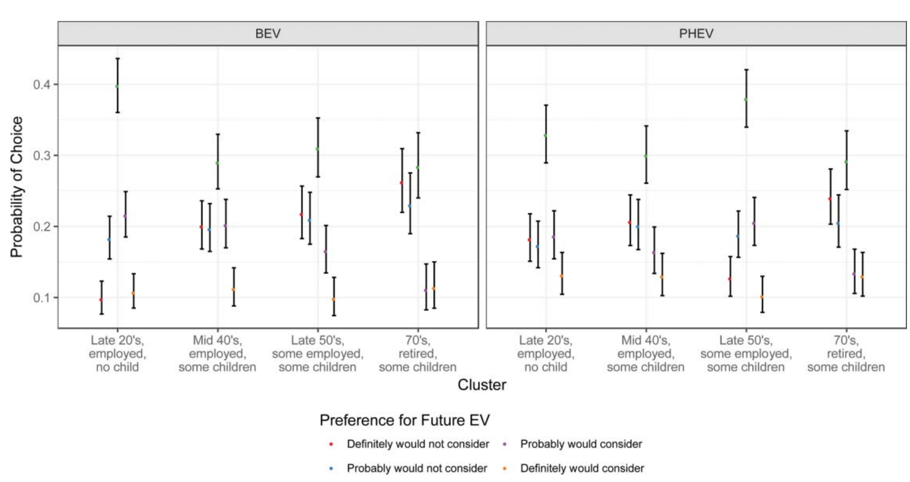

Figure 8. Life-stage cluster and vehicle electrification analysis, predicted probabilities for future BEV/PHEV purchase preferences based on life-stage clusters. Error bars on each line encompass a 95% confidence interval based on the standard errors from the model.

Table 10. Multinomial logistic regression results for life-stage cluster model on adoption of BEVs and PHEVs.

	Life-stage cluster	Definitely would not consider	Probably would not consider	Might or might not consider	Probably would consider
BEV purchase intentions	Mid 40's, employed, some children	0.632***	0.594**	0.238	0.046
		(0.243)	(0.243)	(0.227)	(0.246)
	Late 50's, some employed, some children	0.453*	0.352	−0.073	−0.539**
		(0.234)	(0.235)	(0.219)	(0.249)
	70's, retired, some children	−0.329	0.287	0.361*	0.256
		(0.252)	(0.234)	(0.211)	(0.226)
	Constant	0.311*	0.323*	0.975***	0.539***
		(0.166)	(0.165)	(0.148)	(0.159)
	AIC	6202.013			
PHEV purchase intentions	Mid 40's, employed, some children	−0.243	0.173	0.479**	0.466**
		(0.240)	(0.231)	(0.212)	(0.234)
	Late 50's, some employed, some children	−0.138	−0.164	0.081	0.114
		(0.226)	(0.228)	(0.208)	(0.231)
	70's, retired, some children	0.149	0.023	−0.027	−0.203
		(0.226)	(0.230)	(0.216)	(0.247)
	Constant	0.466***	0.436***	0.838***	0.236
		(0.159)	(0.160)	(0.150)	(0.167)
	AIC	6274.478			

6. Discussion and conclusion

Our analysis on the two car-sharing/ride-hailing mobility surveys allows for unique insight on new mobility services and their relation to preferences for electric vehicles. The primary hypothesis of our study was confirmed: we find a positive relationship between new mobility usage (both car-sharing and ride-hailing) and desire to purchase electric vehicles in the future. Over the body of literature of electric vehicle preferences, our findings are the first to discuss the relation between electric vehicles and new mobility services. We do not conclude whether there are causal effects of these services on the adoption of electric vehicles based on the direct responses in the survey. Car-sharing and ride-hailing experiences with electric vehicles were among the least

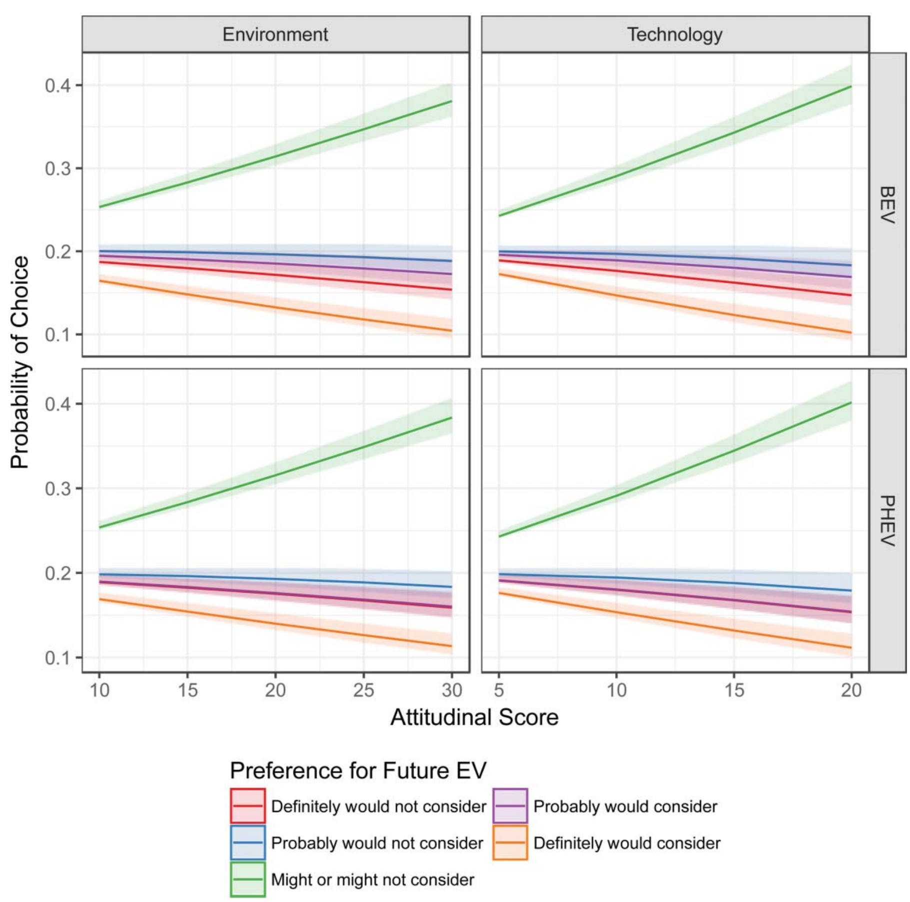

Figure 9. Environment/technology attitudes and vehicle electrification analysis, predicted probabilities for future BEV/PHEV preferences based on attitudinal scores. Higher scores correspond to greater awareness/concern for environmental issues or affinity for newer technologies. Error bars on each line encompass a 95% confidence interval based on the standard errors from the model.

Table 11. Multinomial logistic regression results for respondents environmental and technology attitudes model on adoption of BEVs and PHEVs.

	Attitudinal scores	Probably would not consider	Might or might not consider	Probably would consider	Definitely would consider
BEV purchase intentions	Environmental attitudes	0.00675***	0.0302***	0.00386	−0.0129***
		(0.00238)	(0.00214)	(0.00242)	(0.00267)
	Technology attitudes	0.0110***	0.0499***	0.00697*	−0.0183***
		(0.00400)	(0.00359)	(0.00405)	(0.00444)
	AIC	12688.27			
PHEV purchase intentions	Environmental attitudes	0.00479**	0.0294***	0.000246	−0.0112***
		(0.00238)	(0.00212)	(0.00244)	(0.00261)
	Technology attitudes	0.00768*	0.0481***	0.000141	−0.0160***
		(0.00398)	(0.00355)	(0.00409)	(0.00433)
	AIC	12703.6			

selected options for reasons when considering reasons to purchase an EV in the future. This agrees with the conclusions of the most closely related study by Kim, Joonho, and Yujin (2015) which find characteristics of the EV itself such as noise, speed, and comfort were more important than involvement with sharing programs. However, we do find that among the survey respondents, new mobility services are an important predictive indicator for future vehicle preference. The greater the usage of

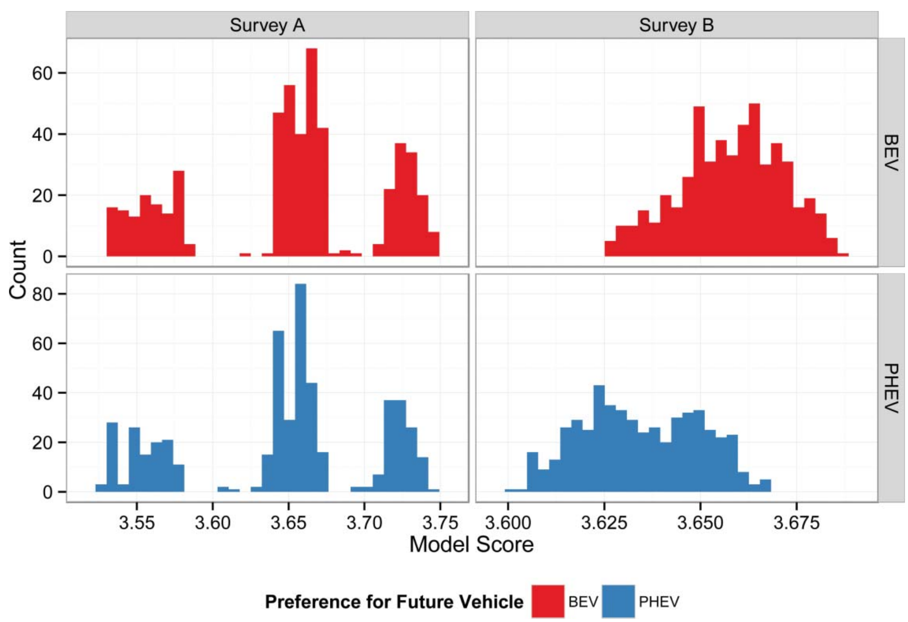

Figure 10. Distributions of cross-validation scores for all possible model prediction combinations.

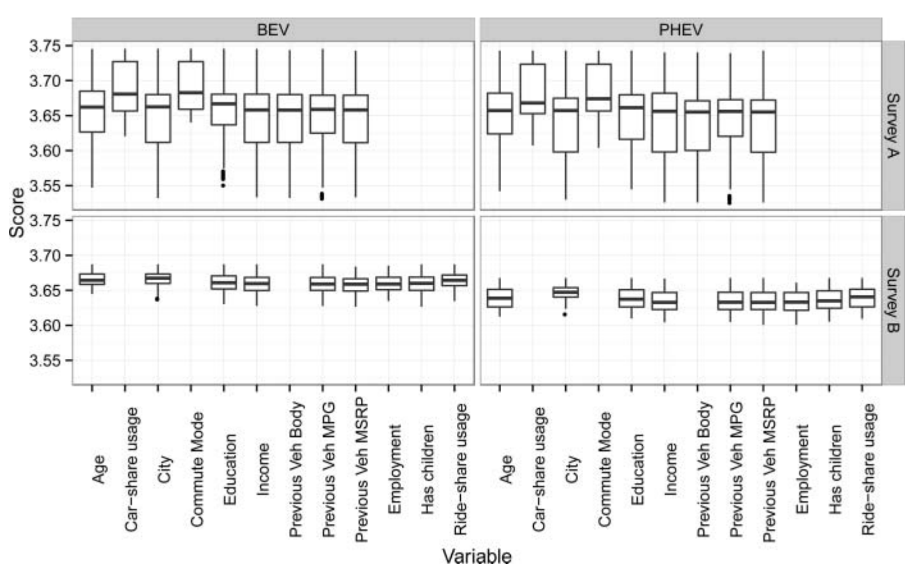

Figure 11. Boxplot of scores for individual variables for cross-validation model.

car-sharing and ride-hailing services, the greater the preference for electric vehicles. At the highest levels of usage of new mobility services, our predicts as high as 55%–70% probability that respondents choose "Probably would consider" or higher to purchase an electric vehicle. The importance of our research is to provide the first quantitative analysis of new mobility service usage and its relation to electric vehicle adoption, something that has been lacking in the literature on electric vehicle preferences. The California Air Resources Board provides additional credits under their Zero Emission Vehicle mandate program for electric vehicles in car-sharing programs (see Rule 5.B. of "Zero-Emission Vehicle Standards for 2009 Through 2017 Model Year Passenger Cars"). Our work provides impetus into the efficacy of this program and potential expansions into ride-hailing services, as well as potential policy levers to help promote electric vehicle adoption in other regions by leveraging new mobility services.

In addition to the findings about car-sharing and ride-hailing effects, we also identified several interesting trends of purchase intentions with MSRP and with environmental and technological attitudes. In the case of MSRP, the increase in the value of a respondent's last vehicle was mean regressing—extreme considerations or non-considerations both decreased while the middle option increased in probability. One possible explanation for this effect could be due to the fact that variation for choices increases with previous vehicle MSRP. If that MSRP is an indication of purchasing ability of future vehicles, then the higher MSRP would correspond to greater flexibility and a mean regressing consideration. We are unaware of literature that examines the value of a car buyer's previous vehicle as an indicator for future purchase intention and further examination of this effect would be a valuable contribution to adoption literature. A similar trend can be found in the analysis on environmental and technological attitudes. The mean regressing behavior is observed as attitudes for both attributes increase in score. This could be a result of the attitudes leading to greater "openness" for the technology, but not necessarily a complete affirmation of electric vehicles.

Our study is confined by some limitations of the survey method. The results are dependent on sampling methods of the surveys and thus are not representative of the true population of the sampled areas. Our respondents tended to be older, more educated, and relatively higher income. In addition, the study area heavily favors urban and suburban areas of major metropolitan cities in the United States, it is likely that the results would differ for more rural populations or different countries. While there is certainly potential to extend the results by surveying different alternative populations, a deeper dive into the relationship between electric vehicles and new mobility services is likely of more interest.

As new mobility service usage is rapidly evolving, both in variety (pooling services and newcomers to the scene) and popularity, users of the services are constantly in flux. Future research to understand how the expansion of these services will affect electric vehicle preferences will be a critical area of study. One potential topics of interest is how different types of services relate to electric vehicle adoption. Are users of pooling services different from users of more taxi-like services? Another topic ripe for study is whether the results from our analysis still hold as different users adopt new mobility services, particularly as the services enter more mainstream markets and are differentiated from early adopters of the technology.

We hope that in addition to our contribution on understanding preference and adoption of electric vehicles, the introduction of new mobility to the conversation will encourage further research in this area.

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